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An Art of Review: Fruit Ripeness and Quality Grading Detection Using Deep Learning

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Abstract:- Accurate detection of fruit ripeness and quality grading are crucial for modern agriculture, as it significantly influences market value, consumer satisfaction and postharvest losses. This overview of the paper examines the latest progress in ripeness detection and quality assessment by deep learning. Although traditional techniques were once dominant, they demonstrate limitations on scalability and accuracy under diverse environmental conditions. Besides machine learning and deep learning, especially with convolutional neural networks (CNN) and models based on YOLO, there's a lot of potential for better performance. This paper focuses on using multiple labels to sort fruits by how ripe they are, their size, and their quality level, following international standards like USDA and APEDA. This review also points out some important datasets and talks about the challenges, like how changes in the environment can affect things. In future, it proposes the development of generalized, multi-fruit detection models for real-time deployment, with potential applications in smart farming and automated fruit pricing systems.

Keywords: *Fruit Ripeness, Grading, CNN, YOLO.*

1. Introduction

Fruits are one of the edible foods that are widely grown and cultivated worldwide. Sources such as the Food and Agriculture Organization (FAO) claim that fruit production is 2 billion metric tons worldwide, and Asian countries are leading producers. Agriculture can contribute to the nation's economy. Fruits are considered the most important nutrient-dense foods [1]**.** Fruits are nutritious for our health, but the fluctuation in maturity and quality standards can affect the majority of consumer production in the import/ export trade. Previously, FAO claimed that there was almost a 19% annual loss in fruits, which thereby impacted the Indian economy drastically.

Fruit maturity follows stages from bud, flower, mid-growth, fully matured, and over-matured [2]**.** Essential aspects defined for fruits were based on their size(weight), color, and quality, which are determined by traditional techniques. Chemical, physical, and physiological parameters are discussed by various procedures and experiments in defining ripeness states. Even hyperspectral imaging and NIR sensors were focused to adapt with environmental conditions [3][4]. Meanwhile, manual inspection showed limitations to complexity on new inputs for variation in background, resulting in reduced performance metrics [5]. Thus, in a complex environment, there were limitations to achieving [6][7].

Over-ripeness or over-maturity of fruit in ripeness stages affects high-quality standards, which can become a concern to avoid during export to vendors through the cultivation field. For which early determination of fruit in altering of over ripeness can reduce some losses to meet the quality grading standards in the market [8]. Smart technology in the 21st century has come up with innovative solutions to resolve agricultural problems. The transition from traditional models to ML algorithms has been useful in extracting features from the fruits using algorithms of regressions and classifiers like Support Vector Machine (SVM), Random Forest(RF), and Gradient Boost (GB) for ripeness detection [9]. Later researchers found that by comparing it with deep learning models, it surpasses the basic model in their performance metrics [10]. The accuracy of CNNs is higher compared to SVM [11] and also against Naïve Bayes, Gradient Boost [12]. The CNN models benefit from feature engineering handled through algorithm optimization and also, it could recognize parameters in fruits such as quality, ripeness score [13][14].

This study review will focus on the advancements of ripeness and quality standards in fruits through deep learning techniques by analyzing various articles relevant to this. Further research will be emphasized on how multi-fruit can be created to predict accurate results for the right stages of ripeness and grading quality assessment when they are combined. An Analysis was conducted with the previous article and our article to determine fruit ripeness and quality grading, as described in Table 2. A '✓' represents the presence, and a '×' represents absence for the given article discussed in Table 2. The researchers found that the models could not resolve the complexity of multi-fruits for ripeness and grading quality together. The capability to handle the task of feature engineering by algorithm optimization was a benefit of using deep learning models. As part of deep learning CNN, it could classify and locate the presence of fruits by its bounding box feature, which helped in doing tasks such as detection, classification, and segmentation [15].

The sectional overview is briefed as follows:

Section 2, survey methodology, is described by the selection of relevant papers through the PRISMA approach. The following Section 3 defines different stages of fruits used by various researchers and tabulates quality grading standards. Some datasets relevant to the ripeness and grading of fruits are described in Section 4. Discussion about various techniques used is addressed in section 5, followed by performance metrics, results, and challenges faced, and suggests a possible future direction in resolving them in section 6. At last, the conclusion of our paper is wrapped up in section 7.

2. Survey Methodology

The selection of papers included the criteria described below in Table 1, which covers the papers that are not duplicates or unrelated papers. The survey of papers involved high-quality databases such as SpringerLink, ScienceDirect, and IEEE Xplore, which provide comprehensive research on relevant papers. During the research phase, we found 342 papers that were related to information that considers the conditions on a broader topic. By using the PRISMA approach, our research was confined to 47 papers dedicated to the specified to the given topics of the review paper.

Table 1. *Criteria for selecting papers*

Type of study	Review, Research papers
Baseline	Deep Learning
Key Terms	Fruit Ripeness, Grading
Text Language	English
Publication Year	2018 to 2025
Sources	Journals and Conference papers

3. Fruit Ripeness Stages and Quality Standards

Ripeness is the stage of fruit when the fruit is edible. Several stages are defined for the classification of fruit ripeness, which are mainly unripe, ripe, and overripe. Many articles explain these based on grading levels, where early levels are for unripe and higher levels tend to overripe [21]. Some researchers have discussed 3 stages [22], 4 stages [23], 5 stages [2], 6 stages [9], and even multiple stages [24], either on specific fruit or on a maximum of 3 fruits. While determining the quality of fruits, ripeness is just a small part of it, the main focus is shifting to the size/weight, quality of grade standards that can affect the import/ export trade. Prominent quality standards are USDA, UNECE, APEDA, and Codex Alimentarius.

4. Paper Analysis and Datasets Involved

Various articles discussed from 2020 to 2025 are about how ripeness and quality standards help in playing an important role in determining its purpose of use, suitable model, and predicting the state of output. In Table 3, use datasets to approach topic review and how they helped predict appropriate models. Even a limitation column is added where they lacked.

Table 2. *Comparison Of Existing article with our proposed article*

References	**Explained**				**Challenges & future directions**	**Novel Contribution of the Paper**
	Datasets	***Models***	***Ripeness***	***Grading***		
Brasil et al. (2018) [16]	×	✓	×	✓	×	It focuses on the main factors that could influence them and provides ways by which freshness, firmness, and color can be maintained.
Kumar et al. (2021) [17]	✓	✓	×	✓	✓	A Fruit-CNN architecture is proposed for identifying fruit types and quality assessment for real-world images.
Barbole et al. (2023) [18]	✓	×	✓	×	×	It uses 4 different grape vineyard datasets for detection, segmentation, and weight prediction of grape clusters.
Alaudeen et al. (2024) [19]	✓	✓	×	×	×	An approach of image processing through depth-based is proposed for self-picking apples.
Khatun et al. (2024) [20]	✓	✓	✓	✓	✓	An automated system with high resolution for dragon fruits is introduced for optimal harvest time and ensuring the freshness of fruit quality.
Sikder et al. (2025) [12]	✓	✓	✓	×	✓	It discusses the most efficient model by comparing other baseline models.
This study	✓	✓	✓	✓	✓	It will focus on ripeness, quality grading, and size tolerance, which would help modern smart agriculture.

Table 3. *Paper Analysis From 2020 to 2025*

References	Datasets	Models	Results	Limitations
Duong et al. (2020) [25]	Fruit-360 dataset	Efficient Net, Mix Net	Accuracy: 95 %	Scalability issues and controlled image conditions.
Kumar et al. (2021) [17]	FruitGB dataset	Fruit-CNN, MobileNet-v2, ResNet-50-v2, VGG 19	Accuracy: 99.6 %	Internal quality not determined.
Nithya et al. (2022) [26]	Mango dataset	CNN + Weiner Filter	Accuracy: 98.5 %	Defect types, generalization restriction on dataset size.
Meshram et al. (2022) [13]	FruitNet dataset	CNN, ResNet-50	Accuracy: 89 % on classification & 85 % on quality detection	The advanced model is not used. Lacks annotation for ripeness stages.
Mamat et al. (2022) [27]	Oil Palm FFB dataset	YOLOv3, YOLO v4, YOLOv5	Precision : 96.7 %, Recall : 97.5 %, mAP : 98.7 %, FPS : 0.3 ms	High computational cost.
Sultana et al. (2024) [28]	XAI-FruitNet dataset	XAI-FruitNet+Hybrid Pooling, VGG16, MobileNetV2, ResNet50, EfficientNetB0, GRAD-CAM	Accuracy : 99 %, Precision : 97.2 %, Recall : 97.3 %, F1-score : 97.3 %	Model speed reduced due to explainability. Defect detection robustness is limited.
Sikder et al. (2025) [12]	Mangoes (Himsagor) dataset	Gaussian Naïve Bayes, SVM, GB, RF, KNN, CNN, VGG16	Accuracy: 96.2 % with Gradient Boosting	The dataset imbalances, background conditions are limited.

5. Techniques Used in Fruit Ripeness and Quality Grading

Various techniques that were part of research in fruit ripeness and quality standards over the past years, whether we discuss traditional methods of manual inspection, hyperspectral imaging, or improvement of performance through machine learning methods, then computer vision models and deep learning techniques in helping predict results at their stages and grading standards. In the subparts below, we discuss how each method helped in our article.

5.1 Traditional Methods and Machine Learning Models

An approach of image processing in feature extraction by using the HSV color space in mango fruits, which was altered to determine ripeness stages [29]. Another approach to the same fruit (mango) was considered through a traditional method, as Electrical Impedance Spectroscopy (EIS), which contributed to the solution of the non-visual approach [30]. Even the addition of numerous imaging techniques was used to improve the quality of fruit [31][32]. But tedious work and low accuracy of detection when compared to machine learning models made a shift towards them. Regression and classification algorithms had been used for the detection. Some of the papers used transfer learning in addition to an ML model to improve their prediction accuracy [33].

5.2 Deep Learning Models

In recent years of research, the researchers have focused on using deep learning models rather than use of machine learning, which were an approach taken in predicting ripeness and grading because of a reason that it provided higher performance in mean average precision in the output layer. Not only that, even when used with a fast recurrent network, which is capable of learning features by passing through multiple layers of the network, its latency was seen to be higher, which outperformed the baseline model of machine learning algorithms. Some newer deep learning models have shown really good results, and because of that, more people are starting to use them, especially when it comes to detecting objects. Continuing that, in deep learning, there are many articles focusing on CNN and YOLO models.

5.3 CNN Models

A Convolutional Neural Network (CNN) is an architecture of deep learning that evaluates from visualized images provided as input and then allows them to pass through multiple channels of layers in its network, depending upon the number of images as input, and again adjusts its weights to come up with a single channel of output. Due to its multi-layer architecture, it helps in eliminating noise that can affect the architecture and helps in optimizing the accuracy of its prediction. There are various models used by research papers depending on the dataset size and parameters used, such as AlexNet, Inception, and VGG on different versions by use of Keras and TensorFlow frameworks for model building and evaluation [26][34].

ResNet and Faster-RCNN were used in articles, which had the ability to use a residual function that could alter weights without degrading the model during training, which could help in performance improvements [13][35]. An application in real-time was used in an article on a strawberry fruit to determine accuracy and inference speed when tested with real-world scenario conditions [36].

These models could come up with faster inference time for a small dataset or fewer features involved. But some recent papers show that when a complex environmental background was considered, with more features added. These models fail to maintain the same accuracy as previously achieved. Researchers looked for more advanced models that can come up with resolving issues in predicting and improving performance even in complex environmental conditions. Then, with the introduction of YOLO models by Ultralytics, the researchers took up these models and checked whether they outperform the CNN model in performance and inference time or not [37].

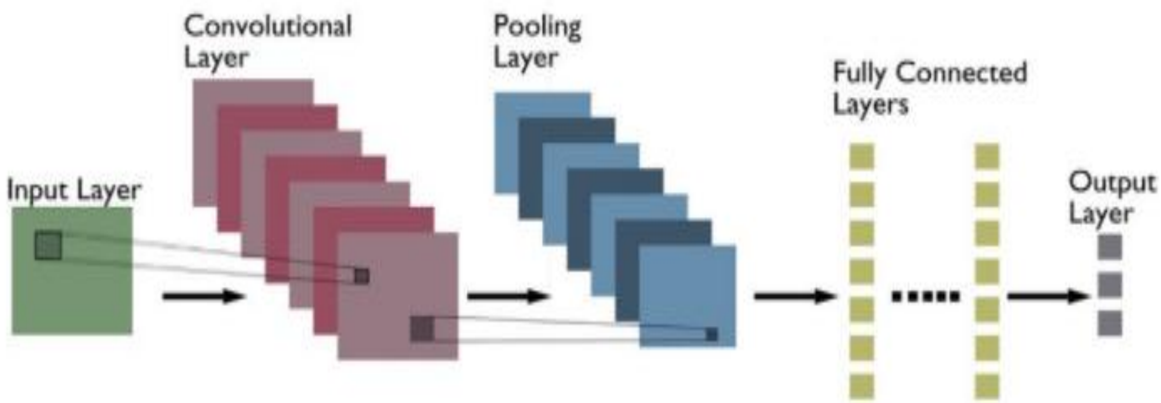

Fig. 1. The Architecture of CNN models

5.4 Models of YOLO

A fruit detection on the real-time system by use of You Only Look Once (YOLO) is described, which eliminates multiple passes over an image. This provides faster and efficient results. This architecture uses a bounding boxes approach by considering images in grids. Each grid in the bounding boxes determines a confidence score, which can help in finding the results of ripeness and quality standards of specific fruits. Due to higher inference speed, in turn reducing time, makes it more feasible to use in real-time applications.

Different versions of models of YOLO have been used over the past years, depending on the problem use case, which are described as follows:

Version 1: Use of a single-shot detection model, allowing a single pass of image preprocessing.

Version 2: Use of anchor boxes in fruit detection with version 1.

Version 3: By using the OpenCV tool in ripeness stages in object detection on a real-time application [38].

Version 4: Helped with the darknet architecture improvement, which was used in the YOLOv3 model[39].

Version 5: Improvement in performance and inference speed over base YOLO version models [40].

Version 7: Improved performance with new object detection techniques using a double-layer approach [41].

Version 8: Enhanced improvement in classification and segmentation models, and providing higher performance [42][43][44].

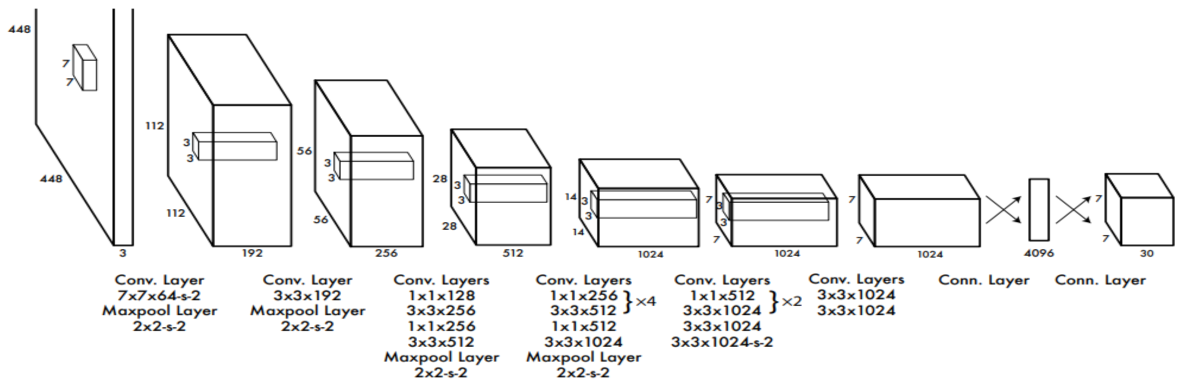

Fig. 2. The YOLO Model Architecture

6. Discussion

Using deep learning models like CNNs and YOLO has shown to be much better at accurately detecting fruit ripeness and grading, compared to older machine learning methods. However, the datasets had some limitations in to use of grading standards criteria such as APEDA, USDA, which had an impact on real-time deployment. So, in determining fruit ripeness prediction and quality grading to the fruits where focus was only on improving accuracy to achieve quick response time by using metrics to determine its output results. By doing so, many terms such as mean Average precision (mAP) [37], Recall [45], Accuracy, F1-score [46], R2-score [41], Inference time [47] have been discussed. But many models have failed in determining the field environment due to fruit overlapping, variation in lighting. Even though it has been limited to specific ripeness or quality prediction architectures, it lacks multi-label architectures. Talking about the future, using multi-label architectures might be a good way to make the model more flexible and better at handling different cases.

7. Conclusion

Using deep learning to combine fruit quality data has really made it easier and more accurate to assess harvested fruits. Through reviews of various methods and technologies, this paper demonstrates the value of multilabel annotations for classifying dataset quality, model selection, and results. Existing models work well in controlled environments, but further testing is required to improve robustness under real conditions. Future directions include combinations of size and quality attributes and forecasts that allow automated pricing and market-ready classification to pave the way for intelligent agricultural solutions.

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